Improving Asset Management and Order Fulfillment at Deere & Company’s C&CE Division

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In 2001, Deere’s Commercial and Consumer Equipment (C&CE) Division, with growing sales of $3 billion, set out to improve its on-time delivery from plants to dealers and to reduce its inventory while maintaining customer service levels. C&CE used state-of-the-art inventory optimization techniques embedded in SmartOps’ multistage inventory planning and optimization (MIPO) product to set trustworthy weekly inventory targets. C&CE used these targets, together with appropriate dealer incentives, to transform to a pull system and exceed its goals. With 2,500 dealers, 100 product families, and a 26-week planning horizon, Deere’s application of multiechelon inventory optimization may be the largest example of applied stochastic inventory theory in practice in a multiagent environment. With the enterprise-wide system integration, Deere improved its factories’ on-time shipments from 63 percent to 92 percent, while maintaining customer service levels at 90 percent. Between 2001 and 2003, Deere reduced or avoided inventory by $890 million, improving annual shareholder value added (SVA) by $107 million. By the end of 2004, the C&CE Division will exceed its goal in $1 billion of inventory reduction or avoidance, a year ahead of schedule.

Key words: industries: machinery; inventory production: policies, review/lead times.

Optimizing inventory in complex supply chains is challenging. Expecting sustainable inventory reductions, many manufacturers, distributors, and retailers have invested in enterprise planning and execution systems but continue to face inventory problems. To make matters worse, increased competition is reducing companies’ profit margins and motivating them to improve return on assets to free up cash for innovation and financial stability. However, they need to make these improvements without sacrificing product availability for an ever-broadening array of products.

Establishing a sustainable inventory optimization system is not simple. The system must balance supply and demand across many levels of production and storage, forms of inventory, and multinational locations in an ongoing manner. In addition, time-varying demands (caused by seasonality, product life-cycles, and promotions) and time-varying capacities (caused by expanding plants, introducing new processes and technologies, holidays, and scheduled shutdowns) make setting reliable inventory targets difficult. When firms share capacity among multiple products, use alternate bills-of-materials, and rely on a variety of production methods, the problem becomes even more complicated. The uncertain nature of demands, production, and lead times magnifies the problem. Solving stochastic, capacitated, multiechelon, multi-product production and inventory models effectively is a difficult operations research problem.

Aside from the mathematical difficulty of solving such a problem, the difficulty of optimizing inventories in the real world is compounded by several factors. Industrial problems often include thousands of items in thousands of locations, making the sheer scale of the problem considerable. Within a single company, groups with different incentives manage inventories across supply chains. To change the way these individual groups manage supply chains, one must change their mind-sets. As products, customers,
and dealers change, inventory targets computed some time ago are no longer optimal, nor feasible, and must change. Decision-support systems require reliable and timely data from many sources, stored in different formats and granularity.

What makes it possible to optimize inventory and sustain improvements today? In the last five years, researchers have greatly advanced computational methods to solve difficult stochastic problems. Investments in planning and execution have enhanced data availability and processes for managing supply chains. Firms can now gather data quickly from a handful of systems. They can automate their processes through flexible interfaces and batch processes running on automated schedules. Web-based software applications harness the computing power of distributed servers, allowing concurrent users to share information, collaborate, and make decisions. Finally, increased processor speeds and inexpensive memory allow computers to solve difficult operations research problems in hours, rather days or weeks. In this paper, we describe an example of sustainable inventory optimization that drives order fulfillment on a dynamic ongoing basis at Deere & Company.

Deere’s Journey from Push to Pull
Deere & Company, founded in 1837 and headquartered in Moline, Illinois, is a leading worldwide producer of equipment for agriculture, forestry, and consumer use. The $15.5 billion company employs 43,000 people and sells its products through an international network of independently owned dealers and retailers. The Commercial and Consumer Equipment (C&CE) Division reported over $3 billion in revenues in fiscal 2003. Its products fall into five equipment lines. The lawn and garden line consists of multiple-product families of riding lawn equipment and walk-behind mowers. The commercial mowing line is made up of several product families of mowers. Golf and turf consists of a broad range of mowers and tractor-mounted aerators. The gator line contains several models of four- and six-wheeled utility vehicles. The tractor line consists of product families of utility tractors. Most C&CE products must be available at the dealers, or customers will buy elsewhere. Approximately 70 percent of the C&CE products have very seasonal demand, with 65 percent of retail sales occurring between March and June.

Catalyst for Change
For decades, Deere pushed inventories to the dealers, booked the revenues, and hoped that dealers had the right products to sell at the right time. Although financing helped the dealers early in the season, it was ultimately up to them to sell their inventories to customers. Inventories continually grew in proportion to sales while returns on assets diminished. The industry-wide practice of pushing inventory had to change. In 2000, Bob Lane became chairman and CEO of Deere, and John Jenkins became president of the C&CE Division. Both recognized that C&CE’s return on assets was too low. In addition, independent dealers had told Mr. Jenkins that they were dissatisfied with C&CE’s delivery performance. Ironically, although dealers had large inventories, they often did not have the right products in stock.

As part of the annual strategic-planning process in early 2001, C&CE’s managers set several ambitious performance targets. The division had an inventory-to-sales (I/S) ratio of 58 percent based on inventories at Deere and at its dealers, which translated to less than two inventory turns. C&CE’s leaders committed to reducing total inventory by $500 million and, as sales increased, to holding inventory dollars constant. Deere expected this avoidance to also be $500 million. Compared to previous projections, this goal meant reducing inventory by $1 billion over five years. Furthermore, C&CE’s leaders committed to delivering products to dealers by the dates requested at least 90 percent of the time by 2005.

How Low Can You Go?
C&CE’s supply chain managers needed to cut inventory levels while improving product availability and delivery performance. In August 2001, C&CE’s order fulfillment group read about inventory optimization successes in Fortune (Seikman 2000) and contacted SmartOps. C&CE and SmartOps formed a team (the authors) to tackle the challenge in a sequential, multi-phase approach.

First, the team conducted an analysis to determine how much to cut inventory levels using a more granular and sophisticated approach. We loaded supply
chain data from three C&CE plants and 25 dealers into SmartOps’ multistage inventory planning and optimization (MIPO) application and calculated optimal inventory targets. We compared these time-varying targets to C&CE’s business practices and found that if C&CE located the correct level of inventory at the right locations during every week of the year, it could maintain service levels and support sales with even less inventory than it projected in the strategic plan. C&CE’s leaders realized that they had a tangible opportunity.

Next, we put the results of the analysis into daily operation. We conducted a simulation of a pull-based order-fulfillment system with 25 dealers. MIPO calculated optimal inventory targets for three months and fed them into a simulated network of plants and dealers. We uploaded actual customer orders into the simulation and calculated the service level these plants and dealers would have provided with the calculated inventory targets. This pilot demonstrated that the dealers could have improved service levels with lower optimal inventories.

During the first two phases of our investigation, we worried about the independent dealers’ reactions to the notion that C&CE might provide them with fewer inventories on credit. We visited a representative sample of dealers, and to our surprise, most were willing to reduce inventory. “I don’t need to stock a lot of equipment. I can just stock enough to meet customers’ needs,” said a dealer from Illinois. Another dealer commented that he had bought the adjacent lot to make room for all of the products. Excess inventory increased dealers’ exposure to theft. We also conducted a detailed survey to determine the correlation between dealer characteristics (for example, geographic location, store size, and distance to competitors) and inventory required for merchandising. We found that the desired merchandising inventories were considerably lower than the amounts dealers had. With this feedback, we were confident that we should optimize inventories on a broader scale. The change from the push strategy to a pull strategy was happening.

The success of the first two phases convinced Deere that it could reduce inventories if it used scientific methods to calculate inventory targets. We still had to demonstrate that C&CE could implement an order-fulfillment process driven by the recommended stocking. With 300 products, 2,500 North American dealers, five plants and associated warehouses, seven European warehouses and several retailers’ consignment warehouses, C&CE’s coordination and optimization of its supply chain might be the largest such example. C&CE implemented MIPO in three work packages. In the first, it set inventory targets for about 2,500 North American dealers and five plant warehouses. In the second, it extended MIPO to cover expensive purchased components that suppliers take three or more weeks to deliver. In the third, it extended MIPO to include seven European warehouses and several retailers’ consignment warehouses. In this paper, we concentrate on the first work package and its results.

### Multistage Inventory Planning and Optimization

We computed recommended stocking levels (RLSs) using MIPO, an enterprise-strength application that solves complex stochastic inventory-optimization problems efficiently. It views a supply chain as a discrete-time, stochastic finite-horizon, time-varying, capacitated multistage model.

#### Model

MIPO represents the material flow in the supply chain as an acyclic-directed graph. In the first work package, all supply chains consist of two stages: (1) dealers’ stocking locations, Deere’s European warehouses, and other retailers’ warehouses, from which customer demand is fulfilled; and (2) stocking locations at the warehouses from which dealers’ orders are fulfilled (Figure 1). Dealers stock on average about 100 products. Each product comes from a unique warehouse. The graph thus consists of about 250,000 stocking locations. In Work Package 1, we aggregated Deere’s European warehouses and other retailers’ warehouses into a single stocking location. The supply chains modeled in the second and third work packages consist of three and four stages.

The model assumes a periodic-review replenishment policy. At each stocking location, dealers or warehouse personnel periodically check the inventory position and place an order to raise its inventory up...
Figure 1: All supply chains in Work Package 1 consist of two stages. Dealers count their inventories using the dealer order code (DOC) unit of measure, whereas warehouses count using the factory product IDs (FPID) unit of measure. The latter is less specific and encourages postponement, which is critical for C&CE.

to the RSL if necessary. Dealers many vary in how frequently they review their inventories.

The model ensures that dealers have enough products available to meet or exceed a prescribed service level. Warehouses can also establish minimum service levels. The lead time on a supply chain path is the time between the placement of an order and its receipt, and it consists of a physical lead time covering transportation and a nonphysical lead time covering order processing, filling a truck, and other delays. This lead time can also be stochastic.

In the model, a stocking location can receive materials from multiple upstream source for the same item and can vary these supply ratios over time. At C&CE, we use this feature to model shifts in production among manufacturing facilities over the planning horizon. A stocking location can also contain bill-of-material information allowing MIPO to convert inputs to outputs, and we model common components together and analyze multiple items produced at a plant together.

Some stocking locations satisfy exogenous demands, and others satisfy demands from downstream stages in the supply chain. The model represents demand at any stocking location for any end item as varying over time and stochastic, with the uncertainty also allowed to vary over time. We exploited this feature because the demand is seasonal and purchases are impulsive, requiring high product availability and a responsive supply chain with a manufacturing lead time of three weeks or less.

The model allows capacities at stocking locations and supply paths to vary over time. During peak seasons, demand often exceeds the plant’s capacity to supply products, and thus MIPO must take capacity constraints into account. MIPO can also efficiently model holidays, planned shutdowns, new-process ramp-ups, and other such events.

Finally, the model can also accommodate additional constraints on time-varying minimum inventory levels by item and location. Deere dealers require merchandising stock for their showrooms.

Solution Procedure

The objective is to satisfy different customer segments with the lowest total investment in inventory (across time and stocking locations). In previous attempts to solve such a comprehensive model, analysts have used deterministic approximations, decomposition into single-stage models, and the sequential use of stationary, uncapacitated solution procedures (de Kok and Graves 2003). In 1998, they were solving large industrial problems in a one-off manner (Lee and Billington 1993, Ettl et al. 2000, Rao et al. 2000).

MIPO uses a fast algorithm that combines recent stochastic analysis results (Swaminathan and Tayur 2003) and permits ongoing use. The high-level procedure consists of four main modules (Figure 2). First, the network-analysis (NA) module parses the network structure and enables efficient later calculations. For example, it determines an ordering of stocking locations to facilitate demand propagation.

Second, the internal-service-level (ISL) module calculates candidate service levels at warehouse stocking locations to satisfy the constraint on minimum service level. It is based on an algorithm that uses information about the value-added structure of items as they flow through the network. Next, the safety-stock (SS) module uses these internal service levels to compute safety-stock requirements at all stocking locations in the supply chain for all periods to ensure that they can provide good service. This module’s flexible and scalable algorithm is the heart of the overall solution procedure (Appendix).

Starting from an initial guess, the algorithm uses an iterative application of the ISL and SS modules to set
Network Analysis Module

Internal Service Level Module

Safety Stock Module

Capacitated Materials and Distribution Requirements Planning Module

Figure 2: The high-level solution procedure consists of four main modules. First the network-analysis module parses the network structure to facilitate later calculations. Second, the internal-service-level module calculates candidate service levels at warehouse stocking locations to satisfy the constraint on the minimum service level. Third, the safety-stock module uses these internal service levels to compute safety-stock requirements at all stocking locations in the supply chain, for all periods. Fourth, the capacitated materials-and-distribution-requirements-planning module translates the input demands into production quantities throughout the supply chain, accounting for time-varying capacities, batch sizes, and different review periods.

safety stocks at near-minimum cost very quickly. With these first-pass safety stocks in hand, the algorithm makes a second pass down the supply chain to compute the distribution of the backlogs that will occur at these safety-stock levels. The RSL for each stocking location and period is the calculated amount needed to meet computed demands and backlogs.

Fourth, the algorithm transfers the target for safety stocks to the capacitated materials-and-distribution-requirements-planning (MRP/DRP) module, which follows the logic of an enhanced MRP/DRP system in translating an input statement of demands into production quantities throughout the supply chain, accounting for time-varying capacities, batch sizes, and different review periods. It produces capacity-adjusted RSLs or it alerts users, identifying the period, item, and stage causing the infeasibility. It also suggests a feasible capacity-expansion solution.

In addition to time-varying RSLs by item and stage, the algorithm produces various inventory components: cycle stock, safety stock, merchandise stock, prebuild stock, physical pipeline stock, time-average physical pipeline stock, and total pipeline stock. They help users to understand its recommendations, lend credibility to the RSLs, and increase the trust of users, who typically are not operations research specialists.

The Order-Fulfillment Process

Every week, C&CE determines weekly RSLs over a 26-week horizon to support the weekly order-fulfillment process (Figure 3), thus computing over 6.5 million RSLs.

(1) Dealers review and update their records on inventory on hand and on order two days prior to receipt of their weekly shipments.

(2) On their weekly shipment days, if their inventories are not at or above the RSLs, the order-fulfillment system automatically generates orders to replenish their inventories by the next shipment.

(3) Dealers can add orders manually for particular customers or events or can reroute orders to different dealer locations.

(4) The system calculates committed delivery dates based on warehouse availability, a function of on-hand inventory and planned production. The system processes manual orders immediately and automatically generates orders weekly on the day that the plant ships to each dealer. In processing orders, the system reserves inventory or future production.

(5) Every day, Deere’s ERP system generates a delivery due list for orders to be shipped from the warehouse, allocating on-hand inventory to orders at that time.

(6) When orders leave the warehouse, the system generates invoices against the dealers, decreases inventory on hand at the warehouse, and increases inventory on hand at the dealers.

To determine weekly RSLs at the dealers and at the warehouses, MIPO requires data on forecasts, forecast error, capacity, and minimum stock requirement at the appropriate level of granularity. Because Deere maintains a corporate forecast by region (for example, North America) and by month only, MIPO performs a preprocessing step to disaggregate the forecasts by dealer and week. At C&CE, dealers make the sales...
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Figure 3: The C&CE order-fulfillment process flow consists of six main steps upon the end of MIPO’s calculations. First, dealers review and update their inventory records. Second, if their inventories are not at or above the RSLs, the order-fulfillment system automatically generates orders to replenish their inventories. Third, dealers can add or reroute orders manually. Fourth, the system calculates committed delivery dates based on warehouse availability. The system processes manual orders immediately and automatically generates orders weekly. In processing orders, the system reserves inventory for future production. Fifth, Deere’s ERP system daily generates a delivery due list for orders to be shipped from the warehouse. Sixth, when orders leave the warehouse, the system generates invoices against the dealers and updates inventory levels in the system.

(1) At a designated time each week, MIPO preprocessing the forecast, forecast-error, merchandising stock requirement, and capacity data, creates the input files, and moves them to the designated directory.

(2) The data loader is configured to “listen” for the input files during a specified period each week. When it receives the input files, MIPO validates and loads the data into the data repository.

(3) When data loading has been successfully completed, the core algorithms validate the input data and optimize the inventory levels.

(4) During postprocessing, MIPO applies a rounding algorithm to obtain integer RSLs.

(5) The system creates a file of RSL values and puts it in a specified directory, ready for processing by the legacy system.

(6) The legacy system processes the file to display the RSLs in the order-management-system screens.

Strategic Planning
As needed, MIPO will compute 13 million RSLs over a 52-week horizon to support strategic planning. The main users of this output are planners, analysts, and managers responsible for filling orders, replenishing stock, or managing inventory. Planners, for

and communicate information about them to Deere by settling their accounts. Some dealers settle their accounts every week on schedule, and others don’t. Although the data are inconsistent, they are the best Deere has as a surrogate for sales with which to estimate demand. MIPO analyzes each dealer’s two-year sales history to compute its share of the regional sales. It uses these fractions to disaggregate the region’s forecast into dealer-specific forecasts. Similarly, it disaggregates capacity data at the factories from month to week.

Deere’s products include high-volume products, such as lawn and garden products, and slow movers, such as golf and turf maintenance-equipment products. Deere must plan for two demand behaviors. It uses an intelligent rounding algorithm to handle slow-moving products. The rounding algorithm provides integer RSLs by setting inventory targets with the highest fractional values to the next integer and rounding the others down so as to respect the aggregate RSLs at the product-line level. MIPO performs this step as a postprocessing step.

To support the creation of the RSLs, MIPO uses a batch process that executes the following six steps (Figure 4).
example, periodically review the RSLs for the warehouses for the planning horizon to check whether the replenishment plans for the plants and warehouses are feasible with respect to the capacity constraints, given the expected orders and service requirements, and to calculate the inventory-to-sales ratios. Analysts create different scenarios to answer what-if questions (for example, what if the service level, forecast demand, or capacity increases? What if the forecast error or lead time decreases?). Analysts also evaluate alternative supply chains (for example, to choose a location for a new distribution center) by creating new supply chains and identifying the impact on inventory levels. Managers periodically review the master-summary and inventory-summary reports to assess the total investment in inventory, the distribution of inventory across stages, and the partition of inventory into on hand and on order.

MIPO’s abilities to model supply chains, manage extensive data, and provide alerts support strategic planning. Supply-chain models can vary from simple two-stage distribution systems to complicated supply chains containing capacitated multistage assembly and distribution systems. Users can view and manipulate the models via local intranet or the Internet. Users can edit input parameters individually, in bulk mode, or by importing data through a data-loading utility. The alert-management system provides feedback on semantic and syntactic errors as users create scenarios in real time or via e-mail. Reports
allow aggregation and drill-down of inventory components on item, location, attribute, and time dimensions (Figure 5).

**Impact at C&CE**

We used an organized process to integrate MIPO into C&CE’s pull-based order-fulfillment process. After the implementation, Deere’s IT group insisted that we put in place a maintenance process to incorporate product upgrades. Deere wanted a sustainable and maintained product, not a one-time custom job at C&CE. One full-time employee of Deere maintains the model and the inputs.

After we installed and integrated MIPO with C&CE’s supply chain systems, C&CE invited dealers to review and modify the inventory targets so that they could get used to the new process. After a few months, C&CE took the next step and changed its inventory financing agreements, offering interest-free financing on inventory only up to the newly calculated recommended stocking levels.

**Inventory Reduction**

We compared C&CE’s 2003 performance to its expected performance in 2003 based on 2001 metrics. C&CE’s inventory optimization initiative using time-varying, trustworthy inventory targets during 2003 reduced or avoided $890 million in inventory (Figure 6). Most of the inventory reduction, measured by averaging the end-of-month levels, occurred at the independent dealers. While C&CE records sales revenue when it ships inventory to the dealers, it bears the burden of financing the dealers’ inventory, and thus reductions in inventory affect its bottom line directly. The $550 million in actual inventory reduction breaks down into $500 million at the dealers and $50 million at the warehouses. Deere wanted to maintain warehouse inventories at their previous levels to take advantage of pooling effects and other benefits of flexible inventory (Table 1).

The reduction in inventory meant that revenue bookings dropped. However, Deere still received cash

![Graph showing inventory components](image)

**Figure 5:** The graph depicts an example of a projected inventory snapshot for a product group for the week of April 24, 2004 as computed on March 1, 2004. Pipeline stock is the inventory in transit between the plant and the dealers (for the dealers) and in production (for the warehouse). In this example, pipeline stock is larger for the dealers because the transportation lead time is larger than the manufacturing lead time. Safety stock is the inventory held to hedge against uncertainty in demand. Because there is no significant cost savings in holding safety stocks at the plant (because of the holding cost structure), safety stocks are pushed to the dealers. Prebuild stock is the inventory held because of capacity constraints. Because there are no capacity constraints on the supply path from the plant to the dealer, there is no prebuild stock for the dealers. The only prebuild stock occurs at the plant due to manufacturing capacity constraints. Cycle stock is the inventory held to meet the expected demand during the period. Having such clear justifications for having inventories across locations, items, and time have made the RSLs very trustworthy for Deere and the dealers.

![Graph showing inventory reduction](image)

**Figure 6:** The actual average inventory in 2001 for the C&CE Division was $1.3 billion. Assuming no improvements, C&CE predicted an average inventory of $1.64 billion in 2003. However, the actual average inventory in 2003 was $750 million, resulting in inventory reduction and avoidance of $890 million.
Table 1: We broke down savings by product line. Compact tractors and riding lawn equipment make up 76 percent of sales revenue and account for $460 million in inventory reductions.

<table>
<thead>
<tr>
<th>Product line</th>
<th>Inventory reduction ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Compact tractors</td>
<td>250 million</td>
</tr>
<tr>
<td>Riding lawn equipment</td>
<td>210 million</td>
</tr>
<tr>
<td>Utility vehicles</td>
<td>60 million</td>
</tr>
<tr>
<td>Golf and turf maintenance equipment</td>
<td>20 million</td>
</tr>
<tr>
<td>Commercial mowing products</td>
<td>10 million</td>
</tr>
<tr>
<td>Total</td>
<td>550 million</td>
</tr>
</tbody>
</table>

for these sales. In 2001, Deere decided to spread the noncash-revenue effect over the two upcoming years. In 2001, it took a $325 million bookings reduction, and in 2002, it took a $225 million reduction. This major decision required the support of the entire senior leadership. In fact, managers tempered the speed with which Deere reduced inventory because they thought faster reduction, although possible, would cause greater “booking pain” than they were willing to bear at that time.

Shareholder Value Added
This inventory reduction increased shareholder value added (SVA) by $107 million. (SVA is a value-based performance measure of the worth of a project or a company to its shareholders: net operating profit after tax minus the cost of capital from the issuance of debt and equity, based on the company’s weighted average cost of capital.) In short, SVA is a measure of what Deere or any project is actually worth to its shareholders. Deere calculates SVA as the difference between income and charges for the assets, using 12 percent as the charge for the assets. An increase in SVA affects the share price because it indicates increases in real earnings and the price-to-earnings (P/E) ratio Wall Street analysts use to value shares.

Indirect Benefits of Correct Mix
During the peak season (March through May), the reduction in inventory prompted Deere to double the replenishment frequency. However, because of the high volumes during that time, it incurred no additional transportation cost per unit because it could still ship full truckloads. In addition, the amount of aged inventory dropped from about $140 million to less than $50 million, allowing dealers to offer newer models to customers and avoid loss of revenues from discounted inventory, losses that the independent dealers and Deere share. The savings on avoided discounts alone account for over $10 million annually, affecting profits directly.

Deere had always flexed its capacity in the spring to meet anticipated demand. However, it had still maintained high inventory levels throughout the year. With time-varying, trustworthy inventory targets, Deere could capitalize on its manufacturing flexibility. The project further increased its flexibility by improving its operation. We modeled this additional flexibility in MIPO, and it automatically made use of it to adjust inventory targets.

Optimizing inventory reduced working capital and increased dealer service levels. Sales, Marketing, and Operations no longer debate how much inventory to keep and instead base their discussions on modeling and data. They have a governing mechanism for calculating the optimal level of product to maintain at dealers each week of the year. The C&CE Division now sets time-varying inventory targets for each item at each location, positioning the right mix of inventory in the supply chain over time (Figure 7). Furthermore, it breaks this inventory down by purpose, such as safety stock, cycle stock, pipeline stock, and prebuild stock. Factories have increased on-time shipments to dealers from 63 percent to 92 percent while maintaining service to end-customers at 90 percent. C&CE is committed to delivering its products on time in the quantities dealers need instead of requiring them to carry excess inventory.

In fact, several months into the project implementation, a dealer from South Carolina spoke to a Deere manager at a meeting. The dealer thought he needed to stock some G110 garden tractors, but the system indicated that his current RSL for this product was zero. Knowing that the RSLs had just been reoptimized, the manager found that MIPO now recommended that the dealer stock two G110 garden tractors. The manager informed the dealer about the new recommendation. He responded, “Well, two is what I was going to tell you I needed, and now it has happened at the right time without either of us having to do anything. Not a bad system. Right quantity at the right time of the season.” MIPO accurately
predicted that dealer’s needs and the needs of many others, reinforcing their trust in the system.

With inventory now optimized, C&CE leaders know that the organization is maximizing its return on net assets. Supply chain managers can see the root causes of inventory requirements and C&CE can forecast the impact of improvements in the supply chain on inventory. For example, C&CE used the service-level what-if analysis in conjunction with margin information to determine whether service-level targets should be changed.

Conclusions
Deere’s C&CE Division has already reduced and avoided inventory by $890 million, which translates into $107 million in sustained SVA. As reported in Deere’s annual report, the C&CE operating profit in 2003 was $227 million. Although it accounts for less than 25 percent of Deere’s total equipment sales, the C&CE division contributed 32 percent of the operating profits for equipment operations in 2003. C&CE saved on inventory while improving on-time product delivery to dealers from 63 percent to 92 percent and maintaining service level to end-customers at 90 percent. C&CE’s system calculates optimal inventory levels for each item at each location over time, broken down by the reasons for holding that inventory. Both Deere and its dealers win. The integrated system adjusts inventory levels based on changes in the market or the supply chain and provides decision-support analysis so C&CE can pursue supply chain improvement projects with the most impact.

Without reliable inventory targets, Deere might not have reached its goal of reducing inventories. With the safety net of trustworthy numbers that can be constantly updated, it has made the difficult transformation from a push to a pull system. It expects to achieve its original goals a year ahead of schedule and is setting new goals. Deere is leading the way in its industry, and companies from other industries are following suit. The revolution at Deere heralds new victories in supply chain management.

Appendix
The problem at the core of the safety-stock module is to find the safety stocks at every stocking location in each period that satisfy service levels. To analyze the dynamics of the supply chain, we use the following discrete-time model.

Network Model
We modeled the supply chain as a directed acyclic network $G = (V, E)$, where $V_1$ are nodes representing customer-facing stocking locations and $V_2 = V \setminus V_1$ are nodes representing internal stocking locations.

Planning Horizon
We modeled the planning horizon as a set of periods indexed by $t = 1, \ldots, T$. 
Replenishment Policy

Replenishment follows a base-stock periodic review policy. In its review period, node \( j \) checks its inventory position and places an order to raise its inventory up to the stocking level \( s_j \) if its inventory position is currently below that level.

Review Frequency

A node \( j \) may not review its inventory every period. We denoted the number of periods between two reviews (PBR) by \( P_j \).

Batch Size

If node \( j \) has a batch-size requirement, the order quantity must be a multiple of that batch size, an integer denoted by \( Q_j \). If there is no batch-size requirement, let \( Q_j = 0 \).

Service Level

We defined the service level at node \( j \) as the nonstock-out probability and denoted it by \( \alpha_j \). For customer-facing node \( j \), the user defines \( \alpha_j \). For internal node \( j \), the internal service-level module of the algorithm computes \( \alpha_j \).

Lead Time

The lead time of arc \((i, j)\) is the time between node \( j \) placing an order with node \( i \) and its receipt by node \( j \). It is denoted by \( L_{ij} \).

Multisourcing

A node \( j \) may have multiple suppliers. A multisourcing node places a fixed portion of its order with each of its suppliers, say node \( i \), according to the time-varying sourcing \( r_{ij} \). If node \( j \) has only one supplier \( i \), \( r_{ij} = 1 \). If node \( j \) is a multisourcing node, let \( \sum_{i \in (i,j) \in E} r_{ij} = 1 \).

Bill of Material

For arc \((i, j)\), we denoted the bill of material information specifying the number of units of product stored at node \( i \) needed to make one unit of product stored at node \( j \) with \( \beta_{ij} \).

Demand

We modeled the demand at a customer-facing node \( j \) in period \( t \) as an independent, nonstationary, normally distributed random variable, and the mean and the standard deviation of the demand random variable \( d_{jt}, t = 1, \ldots, T \), are \( \mu(d_{jt}) \) and \( \sigma(d_{jt}) \), respectively.

Service Time

The demand often need not be satisfied immediately but can be satisfied within a time interval, referred to as the service time \( W_j \).

Algorithm

Ignoring time-varying multisourcing, we based the safety-stock module on the following analysis. Let the main decision variable be the safety stock

\[
s = \{s_j | \forall j \in V, t = 1, \ldots, T \}.
\]

Given safety stock \( s \), we want to ensure that \( f_j(s) \), the nonstockout probability at node \( j \) given the above model, meets or exceeds the prescribed service level \( \alpha_j \).

For all nodes \( j \) and periods \( t \), let \( S_{jt} \) be the deterministic variable representing the stocking level of node \( j \) in period \( t \), let \( D_{jt} \) be the random variable representing the demand at node \( j \) in period \( t \), and let \( O_{jt} \) be the random variable representing the order quantity of node \( j \) in period \( t \). The algorithm consists of the following steps:

1. Given the required minimum service level at \( j \), \( \alpha_j \), start with a set of stocking levels \( S = \{S_{jt} | \forall j \in V, \forall t \} \), for example, \( S_{jt} = 0 \). Propagate the demand by setting the mean and standard deviation of demand random variable \( D_{jt} \) to \( \mu(d_{jt}) \) and \( \sigma(d_{jt}) \) when node \( i \) is a customer-facing node or to the mean and standard deviation of the orders downstream from node \( i \) when node \( i \) is an internal node. Then, calculate the mean and standard deviation of the random variable \( O_{jt} \), representing the orders, based on the replenishment policy. In other words, let

\[
D_{jt} = \begin{cases} 
  d_{jt}, & i \in V_1, \\
  \sum_{j \in (i,j) \in E} \beta_{ij} r_{ij} O_{jt}, & i \in V_2, 
\end{cases}
\]

and

\[
O_{jt} = \begin{cases} 
  (S_{jt} - S_{jt-1} + \sum_{h=1}^{P_i} D_{jt-k})^+, & \text{if } t \text{ is a review period of node } i, \\
  0, & \text{otherwise}.
\end{cases}
\]
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(2) Calculate new stocking levels \( S'_{jt} \) starting from the top of the supply chain and moving the calculation downstream. \( S'_{jt} \) solves the equation

\[
\text{Pr}[X_{jt} \leq S'_{jt}] = \frac{1}{Q_j} \sum_{n=0}^{Q_j-1} \text{Pr}[X_{jt} \leq S'_{jt} + n] = \alpha_j \quad \text{if } Q_j > 0.
\]

(a) If node \( j \) is a root of the network \( G \),

\[
X_{jt} = \sum_{k=0}^{L_{jt} + P_j - W_j - 1} D_{jt_i} + B_{jt}.
\]

(b) Otherwise,

\[
X_{jt} = \sum_{i \in (j, i) \in E} \sum_{k=0}^{L_{ij} + P_j - W_j - 1} r_{ij} D_{jt_i} + B_{jt}.
\]

The demand is fully backlogged at every node in the supply chain, and \( B_{jt} \) is the backlogged order from node \( j \) at node \( i \), \( B_{jt} = \sum_{i \in (j, i) \in E} B_{ij} \).

If \( P_j = 1 \) and \( Q_j = 0 \), \( B_{jt} \) has the following form,

\[
B_{ij} = \frac{b_{ij}}{\beta_{ij}} (X_{jt} - S'_{jt})^+ = \frac{b_{ij}}{\beta_{ij}} \max\{X_{jt} - S'_{jt}, 0\},
\]

where \( b_{ij} \) is the backlog allocation ratio for node \( j \). This \( b_{ij} \) is needed when \( i \) has more than one downstream node to supply and depends on the back-order policy at node \( i \). For example, if we choose to allocate the shortfall equally, \( b_{ij} = 1/\text{the number of successors of node } i \). The calculation of \( B_{jt} \) is more complicated when \( P_j > 1 \) or \( Q_j > 0 \).

(3) If \( S'_{jt} \neq S_{jt} \) for some \( j \) and \( t \), let \( S = S' \) and go to Step 2. Otherwise, compute the safety stocks \( S_{jt} = S_{jt} - \sum_{i \in (j, i) \in E} \sum_{k=0}^{L_{ij} + P_j - W_j - 1} r_{ij} \mu(D_{jt_i} + k) \forall j, \forall t, \) and stop.

The complexity of a single iteration of the algorithm is \( O(T \cdot |E|) \). A faster algorithm is not possible because this is a nonstationary model with \( T \) periods and demand propagation occurs along all arcs. In fact, the maximum number of iterations is the number of echelons in the supply chain, which is significantly lower than the number of stocking points or arcs in any real supply chain. If one seeks only safety stocks, the algorithm needs only a single iteration.

Three extensions are worth mentioning. The convergence of the algorithm is guaranteed if all the random variables are independent and normal. For general distributions, this procedure provides a good starting point for a search algorithm, such as infinitesimal perturbation analysis which can handle several distributions. It is possible to incorporate capacity by using shortfall distributions, which can be convoluted appropriately with the distribution of \( X_{jt} \) above. For a fill-rate measure, one can convert to nonstockout probability once the demand distribution is known.

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References


John Jenkins, President, Commercial and Consumer Equipment Division, Deere & Company, said: “Now, three years into this five-year strategy, we have achieved 90% of our goal and are on target to exceed our $1 billion asset reduction goal by the end of this year—one full year ahead of schedule. Our factories and our supply chain are continuing to build closer to demand and we are setting our sights on another significant reduction in assets by 2008.”